

Intellectual capital forecasting for invention patent through machine learning model

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Abstract

Purpose – This research explores support vector machine (SVM) with Gaussian radial basis function kernel (RBF) as the model and Analysis of Variance (ANOVA) for forecasting the invalidation re-examination decisions of China invention patents, it is beneficial to support patent monetization for corporate intellectual capital.

Design/methodology/approach – There were 8,666 China invention patents with their existing invalidation re-examination decisions during 2000~2021 chosen to conduct classification model training and prediction for the accuracy of invalidation re-examination decisions through SVM with RBF. Statistical significance was performed by ANOVA to identify indicators for these invention patents selected in this research. These selected 8,666 China invention patents were divided into two groups based on their invalidation re-examination decisions during 2000~2021 in Table 1, which Group 1 included 5,974 invention patents with all valid or partially valid claims, and Group 0 included 2,692 invention patents with all invalid claims. Thereafter, each group was further divided into sub-groups based on 13 major regions where the applicants filed invalidation re-examination. The training sets for Group 1, Group 0 and the sub-groups were selected based on the patent issued in January, February, April, May, July, August, October and November; while the prediction sets were selected from the invention patents issued in March, June, September and December.

Findings – The training and prediction accuracies were compared to the existing invalidation re-examination decisions. Accuracies of training sets were ranged from 100% in region 7 (Beijing) and region 9 (Shanghai) to 95.95% in region 1 (US), and the average accuracy of invalidation re-examination decisions was 98.95%. While the accuracies of prediction sets for Group 1 were ranged from 100.00% in region 7 (Beijing) to 90.78% in region 13 (Overseas-others), and the average accuracy of classification was 95.96%, this research's outcomes confirmed the purpose of applying SVM with RBF to predict the patentability sustainability.

Originality/value – This research developed an empirical method through SVM with RBF to predict patentability sustainability which is crucial for corporate intellectual capital on patents. In particular, the investments on patents are huge, including the patent cultivation and maintenance, developments into products or services, patent litigations and dispute managements. Therefore, this research is beneficial not only for corporation, but also for research organisations to perform cost-effective and profitable patent strategies on intellectual capital.

Keywords Invention patent, Patent invalidation re-examination, Analysis of Variance (ANOVA), Support vector machine (SVM), Gaussian radial basis function kernel (RBF)

Paper type Research paper

1. Introduction

Knowledge-driven companies pay great attention to intellectual capital (Rastogi, 2000). Intellectual capital gets generated from intangible assets like knowledge (Jardon, 2015). Knowledge process can support intellectual capital to conceptualize knowledge-based assets

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and create competitive advantage (Yang *et al.*, 2015). These intangible assets are the key drivers that ensure competitiveness of companies (Tsui *et al.*, 2014). Patent is one type of intangible assets that constitute or generate intellectual capital, which is important for knowledge-driven companies. Therefore, studies exploring this bidirectional relationship (Garcia-Perez *et al.*, 2020) are viewed as constructive. Patent monetization can structure revenue profiles for optimal profits and creation of intellectual capital. This study focuses on patent sustainability by using machine learning to predict decision of invalidation re-examination, which is one type of re-examination processes and particularly designed for issued patent in China. The outcome of invalidation re-examination is vital for patent monetization.

To cultivate a patent and maintain the patent globally can cost a fortune. Therefore, the enforcement of patent rights to increase the return on investment is an important issue for companies. There are various ways to enforce patent rights and their monetization, such as selling products or services protected by patents, licensing patents, securitizing patents, leasing patents, tokenizing patents, selling patents, or litigation on patent rights, etc.

Corporates can always generate revenue from patents with or without existing services or products. However, there is a flood of emerging technologies. One specific technology can involve many similar patents seeking exclusivity. Patent owners fight diligently to secure validity, while competitors attack exclusivity from various perspectives to ruin the patent or to limit the scope of patent claims. In real world, patent examination process cannot be perfect under various circumstances, for example, inadequate experience of examiners, time available for comprehensive consideration being too short, or for lack of appropriate tools to search related prior arts, etc. Therefore, patent claims for issued patents are often vulnerable if re-examination procedure is filed.

There have been several landmark patent litigations that ended with extremely high damages awarded for misuse. Polaroid had to pay 909 million US dollars (Los Angeles Times, 1990) to Kodak for patent-infringement of a long-running instant photography technology in 1988. Damages awarded in IGEN v Roche was 505 million US dollars, which involved in US patent no. 5,221,605 titled [Luminescent metal chelate labels and means for detection], US patent no. 6,140,138 titled [Electrochemiluminescent metal chelates and means for detection], US patent no. 6,325,973 titled [Methods and apparatus for improved luminescence assays] and US patent no. 6,451,225 titled [Electrochemiluminescent reaction utilizing amines-derived reductant] as reported by the Court Listener (2022).

Genetech was asked to pay USD 300 million in compensatory damages and 200 million as punitive damages to City of Hope for breach of contract (Horvitz & Levy LLP, 2008). The patented technology was related to the Coax genetically-altered bacteria to produce therapeutic human proteins, such as insulin (McBride, 2009).

Hughes Tool v Smith International was settled for 230 million US dollars, which involved two of Hughes' US patents, US patents no. 3,397,928 titled [Seal means for drill bit bearings] (Hanley and Applegate, 1986) and US patent no. 3,476,195 titled [Lubricant relief valve for rock bits] (Justia, 2003) after litigation that lasted 14 years.

The damage awarded in Exxon v Mobil was 171 million US dollars, for infringement of US patent no. 5,324,800 titled [Process and Catalyst for Polyolefin Density and Molecular Weight Control], which involved metallocene catalysts for better fabrication control and quality of plastics and rubber (Chemical Online, 1998).

Since patents offer handsome economic benefits, patent owners defend their Intellectual Property Rights (IPRs) fiercely, while competitors diligently try to pick flaws to seek revocation of patents through invalidation re-examination in patent offices or complaining of infringement in courts. The motive of this research is to predict sustainability of China invention patents in invalidation re-examination by using machine learning.

There are three types of patents, invention patent, utility model patent and design patent, defined in Article 2 of Patent Law of the People's Republic of China (CNIPA, 2022). The

definition of each type of patent can differ slightly in various jurisdictions. Patent right is one type of intellectual property rights. Fortunately, intellectual property law is followed by international treaties and is well harmonized globally. Therefore, it is internationally accepted patent to be new or involving an inventive step, with the capability for industry application (WTO, 1994). If a dispute occurs, associated with patentability, the standard procedure is filing an application to address the grounds, facts and evidence. Nevertheless, the examination fees must be paid to the patent offices or courts.

2. Literature review

Grimaldi and Cricelli (2019) discussed the value of patents and studied the relationship between innovation and technology development. Many studies have applied artificial intelligence to analyze intellectual property data (Abbas *et al.*, 2014; Baruffaldi *et al.*, 2020; Trappey *et al.*, 2020). Aristodemou and Tietze (2018) applied artificial intelligence methodologies, i.e. machine learning and deep learning, to analyze patent information for discovery of relationships, trends and patterns for decision making. Industry experts recognize the importance of artificial intelligence in patent data analysis. Alcácer and Gittelman (2006) studied patent citation to measure knowledge flow. Chen *et al.* (2018) emphasized the rising trend of deep learning in drug discovery. De Fauw *et al.* (2018) further employed deep learning in retinal disease for diagnosis and referral. Dernis *et al.* (2019) explained the impact of artificial intelligence on top 50 companies in scientific publications, patents and trademarks.

Extant literature has discussed how to select appropriate indicators for patents. However, most have reported only inconclusive outcomes in terms of sample sizes, sources of patents, experience and skills. Carpenter and Narin (1983) studied US patents based on the number of patent citations for 24 technologies. OECD (1984) once commented on the bias of patent indicators, as it can often be affected by various reasons, for example, different technology domains, deviations between national patent systems, jurisdictions, geographic impacts, domestic legal impacts, dynamic economics and cultural differences, etc. Allison *et al.* (2004) examined the relationships between asymmetric litigation on patent-value and indicated that patent disputes often involved higher values. After studying indicators on 813 European patents, Reitzi (2004) discovered that the qualified word counts could contribute to patent validity. Zeebroeck (2007) confirmed the confusions related to patent value and patent indicators in respect of forward citations, patent families, issued decisions, patent oppositions and patent renewals. Arts *et al.* (2012) examined 290 US biotechnology patents from 1976 to 2001 to study patent validity based on various indicators, such as international patent classification, backward citation, forward citation, number of claims and the number of non-patent references. Verhoeven *et al.* (2015) investigated technology novelty and radical impact through patent citation and the related international classifications as patent indicators.

In recent years, China has been the number one country in terms of number of patent applications and patent disputes. However, literature on application of invalidation of Chinese patents data is quite limited. Han *et al.* (2021) found patent invalidation data to be a good supplementary indicator for analyzing China's technology development dynamics. Zhao and Song (2018) once studied innovation in China based on ineffective patent applications for information and knowledge management. However, sample sizes of the previously mentioned research were relatively moderate for comprehensive analysis, and Asian patent information was never studied. That is the motive that triggered this research to study 8,666 China invention patents and the related re-examination decisions from 2000 to 2021. In other words, this research is the first to apply machine learning for investigation of intellectual capital through support vector machine (SVM) with Gaussian radial basis function kernel (RBF) model. By training and predicting the invalidation decisions of these 8,666 China invention patents, this research provides an innovative approach to evaluate patent sustainability.

3. Theory and model

OECD (2019) published a technical report artificial intelligence can help shape policies for improving lives. Agatonovic-Kustrin and Beresford (2000) applied artificial neural network (ANN) modelling in pharmaceutical research. Artificial intelligence encompasses intelligent systems to learn with reasoning and to perceive with action. Nevertheless, Artificial Intelligence can mimic or surpass human intelligence. Machine learning is one of the artificial intelligence systems, which involves developing algorithms and statistical models that enable computers to learn from data and make predictions or decisions. SVM is a supervised machine learning algorithm to find the optimal hyperplane and to classify data points into different categories. SVM can be particularly effective for high-dimensional data. For non-linearly separable data, SVM employs the kernel to map the data into a higher-dimensional feature space where it becomes linearly separable by a hyperplane. The RBF kernel is a popular kernel function for SVM.

Machine learning has widespread applications, such as computer vision, natural language processing, recommendation systems, financial services, health care, cybersecurity and energy, etc. However, there has not been much of research to investigate the application of machine learning in matters related to intellectual capital, particularly patents. Intellectual capital comprises invisible, knowledge-based assets and processes that enhance an organization’s value from both internal and external perspectives (Gajic, 2017). Intellectual property is a superset of intellectual capital with explicit ownership rights (Gajic, 2017). Our aim is to discover whether machine learning can be applied to predict sustainability of patents and patentability, particularly SVM, as a suitable machine learning model for data separation. SVM with RBF is an empirical attempt to test the decision for invalidation re-examination of China invention patent in this research. The outcomes are expected to boost knowledge in the field of intellectual capital.

In this research, Analysis of Variance (ANOVA) is applied to identify significant regions where invalidation re-examination decisions have been filed. ANOVA also applied to test the significant indicators for China invention patents. ANOVA is a well-known statistical tool (Anscombe, 1948) to compare variance across the mean values in different data sets. The generated outcome of ANOVA is the “F-Ratio” (Bailey, 2008).

$$F = \frac{MST}{MSE} = \frac{\sum n_j (\bar{x}_j - \bar{x})^2 / (k - 1)}{\sum \sum (x - \bar{x}_j)^2 / (N - k)} \tag{1}$$

The “F-Ratio” indicates the difference between the within group variances and between groups variances. Whether the null hypothesis is supported or rejected can be tested by ANOVA. If a significant difference exists between the groups, it indicates that the null hypothesis cannot be supported. Nevertheless, a higher F-ratio is observed with the corresponding *p*-value being smaller than 0.05.

SVM is a powerful machine learning model. It is supervised classification of data for estimation of a classification hyperplane and to minimize statistical risk. SVM can deliver a decision boundary of the maximum margins for an ideal separation (Asa *et al.*, 2001). This research selected SVM with RBF as the machine learning model for training and to predict invalidation re-examination of the chosen 8,666 China invention patents.

RBF can provide a nonlinear projection that helps separate data in a higher-dimensional space, if the multiple types of data sets are not separated perfectly by linear classifiers in the original space.

$$\text{Kernel Function : Gaussian Radial Basis Function kernel} = e^{-\text{gamma}|u-v|^2} \quad (2)$$

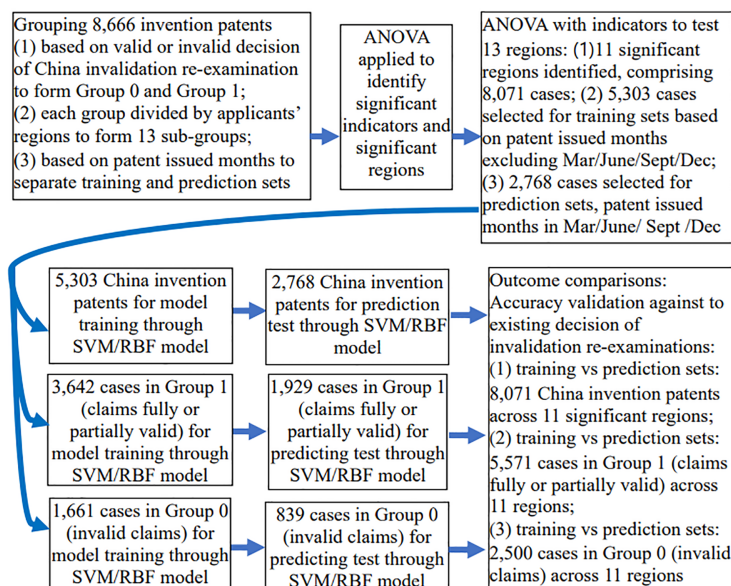
Penalty coefficient cost: 10^6

4. Materials and methods

Flow chart of procedures is depicted in Figure 1.

There were 8,666 China invention patents in respect of which invalidation re-examination was carried out and decisions were given in the period from 2000 to 2021. These were chosen for model training and predictions tests through SVM with RBF, and accuracy against existing decision of invalidation re-examination was tested. Based on the existing decisions of invalidation re-examination in China State Patent Office, these selected 8,666 invention patents were divided into two groups; Group 1 covered 5,974 cases in which claims were found fully or partially valid, and the other was named Group 0 which had 2,692 cases where claims were found totally invalid (Table 1). Thereafter, these selected 8,666 invention patents, Group 1 and Group 0, were further separated into sub-groups based on the regions where their invalidation re-examinations were filed and re-grouped into thirteen major regions (Table 2 and Figure 2).

ANOVA was used for testing the significance of the 8,666 invention patents in terms of eight indicators: number of applicants, number of inventors, number of involved international patent classifications, the number of claims, number of attached figures, number of words in specifications, number of words in abstract and examination duration.



Source(s): Authors' own work

Figure 1. Research procedure and steps flow chart

Table 1. Classification according to the decision of invalidation re-examination

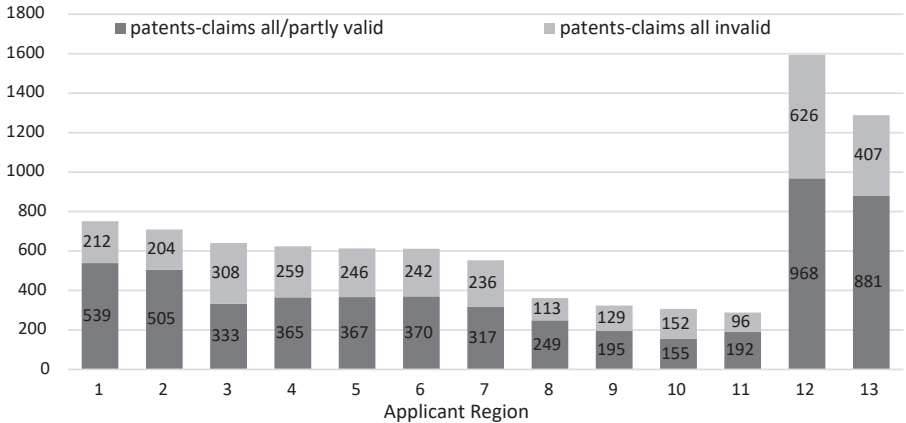
	Invention patents	Label
All claims are valid	3,230	1
Claims are partly valid	2,744	1
All claims are invalid	2,692	0
Total	8,666	

Source(s): The patent re-examination and invalidation department of CNIPA and authors' calculations

Table 2. Region/country statistics of applicants among decision groups

Applicant region	Invention patents classified by decisions of invalidation re-examination invalidation; Group 1 is cases where patents were found partially or fully valid and Group 0 comprises cases where patents were declared invalid		Sub-total
	1	0	
1 (US)	539	212	751
2 (JP)	505	204	709
3 (Guangdong)	333	308	641
4 (Shenzhen)	365	259	624
5 (Jiangsu)	367	246	613
6 (Zhejiang)	370	242	612
7 (Beijing)	317	236	553
8 (DE)	249	113	362
9 (Shanghai)	195	129	324
10 (Shandong)	155	152	307
11 (Taiwan)	192	96	288
12 (CN-others)	968	626	1,594
13 (Overseas-others)	881	407	1,288

Source(s): CNIPA patent re-examination committee and authors' calculations



Source(s): Authors' own work

Figure 2. Patent numbers based on decision of invalidation re-examination by regions

Whether SVM with RBF can be a practical tool for predicting invalidation re-examination, i.e. sustainability of the patent and corporate intellectual capital, was also examined.

4.1 General information

Patents are precious assets that strengthen profitability and competitiveness of corporations. Sustainability of patent is vital if huge economic value associated. However, there aren't many flawless patents that can claim market exclusivity. Therefore, invalidation re-examination is often sought by companies to destroy competitors' patents or to limit the scope of patent claims in case of key patents. To attack the flaws in the patents, applicants need to provide facts and evidence that challenge patentability by law. Depending on the jurisdiction and domestic law, applicants can choose to request invalidation re-examination either in patent offices or courts. There are independent boards in most patent offices or courts for re-examination. There is the Patent Re-examination and Invalidation Department in China National Intellectual Property Administration (CNIPA), the Board of Appeal in United States Patent and Trademark Office (USPTO), and the Intellectual Property Trial and Appeal Board in Korean Intellectual Property Office (KIPO). In Germany, there is the Federal Patent Court. In principle, the standard procedure is to file the application for invalidation re-examination in the relevant authority or court. The counter party is then asked to respond. If the applicant is not satisfied with the decision of invalidation re-examination, the next step is to appeal to a designated court.

4.1.1 Data sets selection for statistics of invention patent informatics on re-examination. The samples were divided into two groups for statistical comparisons. The first group is identified with valid invention patents, in which claims were sustained fully or partially. The second group is identified with invalid invention patents, in which claims were found invalid.

Table 1 shows, 5,974 cases that were found fully or partially valid (Group 1); and 2,692 cases that were found invalid (Group 0).

Thereafter, these 8,666 China invention patents were also divided into regional groups based on the region where applicants filed for invalidation re-examination and were re-organized into 13 major regions (Table 2).

In Region 1 (US), 539 patents were put in Group 1, and 212 in Group 0; in Region 2 (JP), 505 patents were put in Group 1, and 204 patents in Group 0; in Region 3 (Guangdong), 333 patents were put in Group 1, and 308 in Group 0; in Region 4 (Shenzhen), 365 patents were in Group 1, and 259 in Group 0; in Region 5 (Jiangsu), 367 patents were in Group 1, and 246 in Group 0; in Region 6 (Zhejiang), 370 patents were put in Group 1, and 242 in Group 0; in Region 7 (Beijing), 317 patents were put in Group 1, and 236 in Group 0; in Region 8 (DE), 249 patents were put in Group 1, and 113 in Group 0; in Region 9 (Shanghai), 195 patents were put in Group 1, and 129 in Group 0; in Region 10 (Shandong), 155 patents were put in Group 1, and 152 in Group 0; in Region 11 (Taiwan), 192 patents were put in Group 1, and 96 in Group 0; in Region 12 (CN-others), 968 patents were put in Group 1, and 626 in Group 0; and in Region 13 (Overseas-others), 881 patents were put in Group 1, and 407 in Group 0.

Regional distribution of the thirteen regions further divided into all or partly valid (Group 1: lower bars), and invalid patents (Group 0: upper bars) are shown in Figure 2.

4.1.2 ANOVA discovery for significant patent indicators. ANOVA was applied (Table 3) to discover the statistical significances of indicators of invalid invention patent (Group 0) and valid invention patent (Group 1).

Eight patent indicators were tested by ANOVA for ascertaining statistical significance: number of applicants, number of inventors, number of involved international patent classifications, number of claims, number of attached figures, number of words in specification, number of words in abstract and examination duration.

As shown in Tables 3 and 4, the significant indicators were number of attached figures with 0.018 as p -value, number of words in abstract with 0.003 as p -value and examination duration with 0.001 p -value.

Table 3. ANOVA descriptive statistics

Patent indicator	Group	Number	Mean	Standard deviation	95% confidence. Interval for mean	
					Lower bound	Upper bound
Number of applicants	0	2,692	1.212	0.506	1.193	1.231
	1	5,974	1.200	0.498	1.187	1.212
	Total	8,666	1.204	0.501	1.193	1.214
Number of inventors	0	2,692	2.607	2.045	2.530	2.685
	1	5,974	2.678	2.220	2.622	2.734
	Total	8,666	2.656	2.167	2.610	2.702
Number of involved international patent classifications	0	2,692	3.532	2.958	3.420	3.644
	1	5,974	3.472	3.065	3.394	3.550
	Total	8,666	3.491	3.032	3.427	3.555
Number of claims	0	2,692	12.865	14.922	12.301	13.429
	1	5,974	12.834	14.313	12.471	13.197
	Total	8,666	12.844	14.504	12.538	13.149
Number of attached figures	0	2,692	6.935	9.776	6.565	7.304
	1	5,974	7.485	10.191	7.227	7.744
	Total	8,666	7.314	10.066	7.102	7.526
Number of words in specification	0	2,692	11339.428	16420.022	10718.874	11959.982
	1	5,974	12045.180	24797.277	11416.243	12674.118
	Total	8,666	11825.946	22532.380	11351.478	12300.414
Number of words in abstract	0	2,692	222.761	77.416	219.835	225.687
	1	5,974	227.893	74.092	226.014	229.772
	Total	8,666	226.299	75.173	224.716	227.881
Examination duration	0	2,692	35.452	29.551	34.335	36.568
	1	5,974	31.951	24.267	31.335	32.566
	Total	8,666	33.038	26.072	32.489	33.587

Source(s): Authors' calculations

Thereafter, these eight indicators were further tested by ANOVA for validation of statistical significance and recorded in thirteen regions (Table 5).

Table 5 indicates the overall distribution of ANOVA statistical significance for 13 regions where 8 invention patent indicators were tested:

Region 1 (US) was further confirmed in terms of number of attached figures, number of words in specification and examination duration and the p -values were 0.004, 0.024 and 0.003, respectively.

Region 2 (JP) was further confirmed in terms of the number of claims and number of words in specification and the p -values were 0.007 and 0.046, respectively.

Region 3 (Guangdong) was further confirmed in terms of the number of claims, number of words in specification and examination duration and the p -values were 0.044, 0.026 and 0.022, respectively.

Region 4 (Shenzhen) was further confirmed in terms of the number of applicants and number of words in specification and the p -value was 0.001 for both.

Region 5 (Jiangsu) was further confirmed in terms of the number of attached figures and number of words in abstract and the p -values were 0.043 and 0.017, respectively.

Region 6 (Zhejiang) was further confirmed in terms of the number of attached figures and number of words in specification and the p -values were 0.011 and 0.046, respectively.

Table 4. ANOVA discovery for invention patent indicators

Patent indicator		Sum of squares	Mean square	<i>F</i>	<i>p</i>
Number of applicants	Between groups	0.3	0.3	1.140	0.286
	Within groups	2172.6	0.3		
Number of inventors	Between groups	9.3	9.3	1.978	0.160
	Within groups	40694.0	4.7		
Number of involved international patent classifications	Between groups	6.7	6.7	0.724	0.395
	Within groups	79667.1	9.2		
Number of claims	Between groups	1.7	1.7	0.008	0.928
	Within groups	1822904.7	210.4		
Number of attached figures	Between groups	563.0	563.0	5.559	0.018*
	Within groups	877478.7	101.3		
Number of words in specification	Between groups	924327328.7	924327328.7	1.821	0.177
	Within groups	4398366823348.0	507660067.3		
Number of words in abstract	Between groups	48874.6	48874.6	8.657	0.003**
	Within groups	48916802.2	5646.0		
Examination duration	Between groups	22745.1	22745.1	33.586	0.001***
	Within groups	5867347.6	677.2		

Note(s): $p^* < 0.05$, $p^{**} \leq 0.01$, $p^{***} \leq 0.001$
Source(s): Authors' calculations

Region 7 (Beijing) was further confirmed in terms of the number of inventors and the *p*-value was 0.006.

Region 8 (DE) was further confirmed in terms of the number of attached figures and the *p*-value was 0.012.

Region 9 (Shanghai) was further confirmed in terms of the number of claims and the *p*-value was 0.023.

Region 12 (CN-others) was further confirmed in terms of examination duration and the *p*-value was 0.044.

Region 13 (Overseas-others) was further confirmed in terms of the number of involved international patent classifications, number of words in specification, number of words in abstract and examination duration and the *p*-values were 0.019, 0.047, 0.004 and 0.001, respectively.

Based on above results, there were 11 significant regions with 8,071 China invention patents having statistical significance for use of the SVM with RBF model for training and prediction: Region 1 (US), Region 2 (JP), Region 3 (Guangdong), Region 4 (Shenzhen), Region 5

Table 5. ANOVA statistics for 8 indicators across 13 regions

Applicant region	Significance Number of applicants	Number of inventors	Number of IPCs	Number of claims	Number of figures	Number of words in specification	Number of words in abstract	Examination duration
1 (US)					0.004**	0.024*		0.003**
2 (JP)				0.007**		0.046*		
3 (Guangdong)				0.046*		0.026*		0.022*
4 (Shenzhen)	0.001***					0.001***		
5 (Jiangsu)					0.043*		0.017*	
6 (Zhejiang)					0.011*	0.046*		
7 (Beijing)		0.006**						
8 (DE)					0.012*			
9 (Shanghai)				0.023*				
10 (Shandong)								
11 (Taiwan)								
12 (CN-others)								0.044*
13 (Overseas- others)			0.019*			0.047*	0.004**	0.001***

Note(s): $p^* < 0.05$, $p^{**} \leq 0.01$, $p^{***} \leq 0.001$
Source(s): Authors' calculations

(Jiangsu), Region 6 (Zhejiang), Region 7 (Beijing), Region 8 (DE), Region 9 (Shanghai), Region 12 (CN-others) and Region 13 (Overseas-others).

4.1.3 SVM model with RBF training and prediction tests based on paired data sets from 2000 to 2021 cross 11 significant regions. After ANOVA statistical significance confirmation, there were 8,071 China invention patents for which invalidation re-examination decisions had been delivered between 2000 and 2021 (Figure 1) There were 5,303 cases in training sets issued in months excluding March, June, September and December, while there were 2,768 cases in the prediction sets issued in March, June, September and December.

These 5,303 invention patents in training sets were further categorized based on their decisions of invalidation re-examination into Group 1 (3,642 invention patents with all or partially valid claims) and Group 0 (1,661 invention patents with all invalid claims).

These 2,768 invention patents in prediction sets were further categorized based on their decisions of invalidation re-examination. Group 1 has 1,929 invention patents with all or partially valid claims, and Group 0 has 839 invention patents with all invalid claims.

Table 6 presents outcomes in terms of number of cases and was generated through two steps: Step (1) SVM with RBF model conducted training across each regional group and each decision group; thereafter, Step (2) the model trained in Step (1) continued to test the prediction sets.

The training set contained patents issued in months other than March, June, September and December, while the prediction sets were selected based on patents issued in March, June, September and December. The model training and predicting tests were conducted for 11 significant regions with 8,071 invention patents across three arms: (1) The overall 8,071 invention patents were divided into training set with 5,303 cases that excluded patent issued in months of March, June, September and December and the prediction set with 2,768 cases issued in March, June, September and December. (2) The 5,571 invention patents in Group 1 with all or partially valid claims in eleven significant regions were divided into training sets with 3,642 cases and prediction sets with 1,929 cases. (3) The 2,500 invention patents in Group 0 with all invalid claims in eleven significant regions were divided into training sets with 1,661 cases and prediction sets with 839 cases.

The accuracy was confirmed by comparing the training and prediction outcomes with the existing decision of invalidation re-examination.

Figure 3 presents the accuracy trends of the training sets and prediction sets in 11 significant regions.

Accuracy of 5,303 invention patents in training sets ranged between 76.49% in Region 4 (Shenzhen) and 63.14% in Region 8 (DE), and the average training accuracy was 70.43%.

Accuracy of model training in 11 significant applicant regions was ranked: Region 4 (Shenzhen) with 76.49% > Region 7 (Beijing) with 73.05% > Region 3 (Guangdong) with 72.84% > Region 13 (Overseas-others) with 72.54% > Region 5 (Jiangsu) with 70.95% > Region 12 (CN-others) with 70.36% > Region 6 (Zhejiang) with 69.82% > Region 2 (JP) with 68.90% > Region 1 (US) with 65.19% > Region 9 (Shanghai) with 64.45% > Region 8 (DE) with 63.14%.

Accuracy of 2,768 cases in the prediction sets ranged between 72.73% in Region 4 (Shenzhen) and 62.83% in Region 7 (Beijing), and the average prediction accuracy was 68.75%.

Accuracy of prediction of 11 applicant regions was ranked: Region 4 (Shenzhen) with 72.73% > Region 12 (CN-others) with 72.43% > Region 5 (Jiangsu) with 70.98% > Region 6 (Zhejiang) with 70.59% > Region 7 (Beijing) with 69.87% > Region 3 (Guangdong) with 68.44% > Region 1 (US) with 67.51% > Region 2 (JP) with 65.45% > Region 13 (Overseas-others) with 65.14% > Region 8 (DE) with 65.08% > Region 9 (Shanghai) with 62.83%.

Region 4 (Shenzhen) was found to be the number one for both training and prediction.

Figure 4 depicts the trends of accuracy in training sets in 11 significant regions. Group 0 has 1,661 invention patents with all invalid claims, while Group 1 has 3,642 invention patents with all or partially valid claims.

Table 6. SVM/RBF training and prediction outcomes by case numbers across 11 significant regions and decision groups of invalidation re-examination

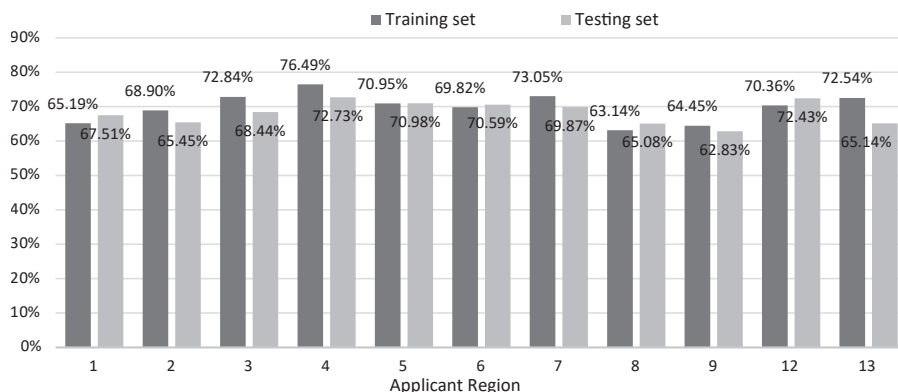
Applicant region	Patent set	Patents	Accurate samples/testing samples		Overall
			Claims fully or partially valid (Group 1)	Claims all invalid (Group 0)	
1 (US)	Training set	474	284/296	25/178	309/474
	Prediction set	277	176/186	11/91	187/277
2 (JP)	Training set	463	290/302	29/161	319/463
	Prediction set	246	154/167	7/79	161/246
3 (Guangdong)	Training set	416	295/300	8/116	303/416
	Prediction set	225	147/157	7/68	154/225
4 (Shenzhen)	Training set	404	290/297	19/107	309/404
	Prediction set	220	154/162	6/58	160/220
5 (Jiangsu)	Training set	420	295/298	3/122	298/420
	Prediction set	193	136/140	1/53	137/193
6 (Zhejiang)	Training set	391	270/271	3/120	273/391
	Prediction set	221	155/156	1/65	156/221
7 (Beijing)	Training set	397	290/290	0/107	290/397
	Prediction set	156	109/109	0/47	109/156
8 (DE)	Training set	236	149/151	0/85	149/236
	Prediction set	126	82/84	0/42	82/126
9 (Shanghai)	Training set	211	135/135	1/76	136/211
	Prediction set	113	71/72	0/41	71/113
12 (CN-others)	Training set	1,039	720/726	11/313	731/1,039
	Prediction set	555	401/403	1/152	402/555
13 (Overseas-others)	Training set	852	553/576	65/276	618/852
	Prediction set	436	266/293	18/143	284/436
Average	Training set	5,303	3,571/3,642	164/1,661	3,735/5,303
	Prediction set	2,768	1,851/1,929	52/839	1,903/2,768
	Total	8,071	5,422/5,571	216/2,500	5,638/8,071

Note(s): Classifying parameters: All indicators of significance respectively for each applicant region
 Training set: patents issued in months excluding March, June, September and December
 Prediction set: patents issued in March, June, September and December

Source(s): Authors' own work

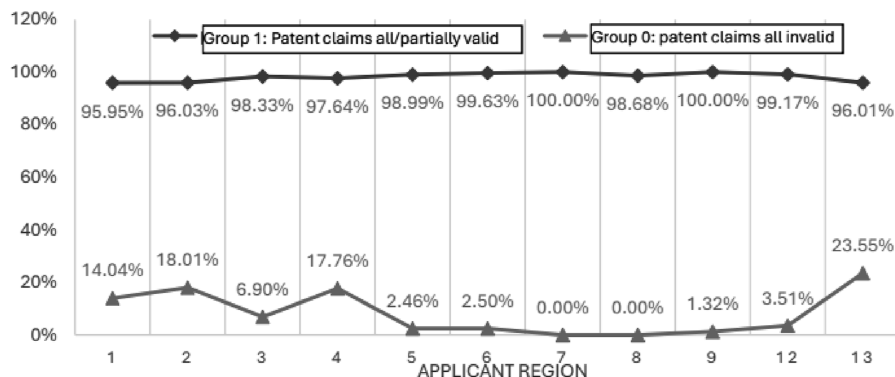
Figure 4 shows that training accuracy for Group 1 ranged from 100% in Region 7 (Beijing) and in Region 9 (Shanghai) to 95.95% in Region 1 (US). The average accuracy of SVM/RBF model training was 98.95% and contributed 3,642 invention patents in Group 1.

Accuracy of models in training was ranked for Group 1: Region 7 (Beijing) and Region 9 (Shanghai) with 100.00% > Region 6 (Zhejiang) with 99.63% > Region 12 (CN-others) with 99.17% > Region 5 (Jiangsu) with 98.99% > Region 8 (DE) with 98.68% > Region 3



Source(s): Authors' own work

Figure 3. SVM/RBF accuracy comparison of training sets and prediction testing sets (%)



Source(s): Authors' own work

Figure 4. SVM/RBF accuracy of training (%)

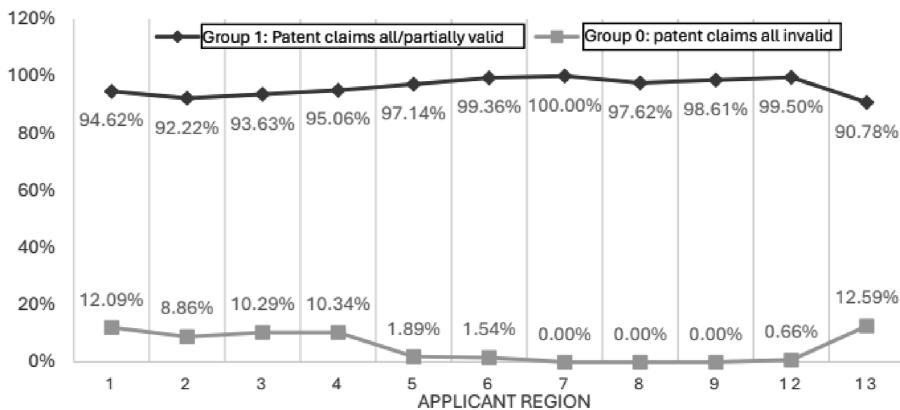
(Guangdong) with 98.33% > Region 4 (Shenzhen) with 97.64% > Region 2 (JP) with 96.03% > Region 13 (Overseas-others) with 96.01% > Region 1 (US) with 95.95%.

Accuracy of training sets for Group 0 ranged from 23.55% in Region 13 (Overseas-others) to 0.00% in Region 8 (DE) and in Region 7 (Beijing). The average accuracy of model classification was 9.78% for 11 significant regions and 1,661 invention patents in Group 0.

Accuracy of models in training was ranked for Group 0: Region 13 (Overseas-others) with 23.55% > Region 2 (JP) with 18.01% > Region 9 (Shenzhen) with 17.76% > Region 1 (US) with 14.04% > Region 3 (Guangdong) with 6.90% > Region 12 (CN-others) with 3.51% > Region 6 (Zhejiang) with 2.50% > Region 5 (Jiangsu) with 2.46% > Region 9 (Shanghai) with 1.32% > Region 7 (Beijing) with 0.00% > Region 8 (DE) with 0.00%.

Figure 5 presents the trends of accuracy of prediction among the 11 significant regions and the invalidation re-examination decision groups. Group 0 has 839 invention patents with all invalid claims, while Group 1 includes 1,929 invention patents with all or partially valid claims.

Accuracy of prediction for Group 1 ranged from 100.00% in Region 7 (Beijing) to 90.78% in Region 13 (Overseas-others). The average accuracy of classification model training was 95.96% in 1,929 invention patents in Group 1.



Source(s): Authors' own work

Figure 5. SVM/RBF accuracy of prediction (%)

Accuracy of prediction was ranked: in Group 1, Region 7 (Beijing) with 100.00% > Region 12 (CN-others) with 99.50% > Region 6 (Zhejiang) with 99.36% > Region 9 (Shanghai) with 98.61% > Region 8 (DE) with 97.62% > Region 5 (Jiangsu) with 97.14% > Region 4 (Shenzhen) with 95.06% > Region 1 (US) with 94.62% > Region 3 (Guangdong) with 93.63% > Region 2 (JP) with 92.22% > Region 13 (Overseas-others) with 90.78%.

Accuracy of prediction sets for Group 0 ranged from 12.59% in Region 13 (Overseas-others) to 0.00% in Region 9 (Shanghai). The average accuracy of model prediction was 6.20% for the 11 significant regions, contributed from 839 invention patents.

Accuracy of prediction was ranked for Group 0: Region 13 (Overseas-others) with 12.59% > Region 1 (US) with 12.09% > Region 4 (Shenzhen) with 10.34% > Region 3 (Guangdong) with 10.29% > Region 2 (JP) with 8.86% > Region 5 (Jiangsu) with 1.89% > Region 6 (Zhejiang) with 1.54% > Region 12 (CN-others) with 0.66% > Region 7 (Beijing) and region 8 (DE) and Region 9 (Shanghai) with 0.00%.

Table 7 was generated from Table 6 and presents percentages of accuracy transformed from accurate case counts vs yearly cases in each data set.

According to Table 7, average accuracy of classification model training was 98.05% for Group 1, 9.87% for Group 0 and 70.43% overall. Average accuracy of the prediction was 95.96% for Group 1, 6.20% for Group 0 and 68.75% overall. In general, accuracy of training sets was higher than the prediction sets.

The average difference between training sets and prediction sets was 2.09% for Group 1, 3.68% for Group 0 and 1.68% overall. These results prove the consistency and further suggest the potential of applying SVM with RBF to forecast the decision of invalidation re-examination for China invention patents.

Nevertheless, the purpose of applying SVM with RBF to support patent strategy of corporate intellectual property disputes by predicting the patentability is achieved. Furthermore, it is beneficial for corporates to manage patented innovation, for example, to adjust the patent litigation strategy by quickly identifying the patent validity. Allison *et al.* (2004) found that patents involved in disputes were highly valued. This research is meaningful for enhancement of corporate intellectual capital, particularly for technology companies.

5. Discussions, implications, limitations and future research streams

In this research, ANOVA was employed to discover the significance of identified indicators and further test the significance in different regions where the cases for invalidation

Table 7. SVM/RBF training and prediction outcomes by percentage across 11 significant regions and decision groups of invalidation re-examination

Applicant region	Patent set	Patents	Classification accuracy (%)		Overall
			Claims fully or partly valid (Group 1)	Claims all invalid (Group 0)	
1 (US)	Training set	474	95.95%	14.04%	65.19%
	Prediction set	277	94.62%	12.09%	67.51%
2 (JP)	Training set	463	96.03%	18.01%	68.90%
	Prediction set	246	92.22%	8.86%	65.45%
3 (Guangdong)	Training set	416	98.33%	6.90%	72.84%
	Prediction set	225	93.63%	10.29%	68.44%
4 (Shenzhen)	Training set	404	97.64%	17.76%	76.49%
	Prediction set	220	95.06%	10.34%	72.73%
5 (Jiangsu)	Training set	420	98.99%	2.46%	70.95%
	Prediction set	193	97.14%	1.89%	70.98%
6 (Zhejiang)	Training set	391	99.63%	2.50%	69.82%
	Prediction set	221	99.36%	1.54%	70.59%
7 (Beijing)	Training set	397	100.00%	0.00%	73.05%
	Prediction set	156	100.00%	0.00%	69.87%
8 (DE)	Training set	236	98.68%	0.00%	63.14%
	Prediction set	126	97.62%	0.00%	65.08%
9 (Shanghai)	Training set	211	100.00%	1.32%	64.45%
	Prediction set	113	98.61%	0.00%	62.83%
12 (CN-others)	Training set	1,039	99.17%	3.51%	70.36%
	Prediction set	555	99.50%	0.66%	72.43%
13 (Overseas-others)	Training set	852	96.01%	23.55%	72.54%
	Prediction set	436	90.78%	12.59%	65.14%
Average	Training set	5,303	98.05%	9.87%	70.43%
	Prediction set	2,768	95.96%	6.20%	68.75%
Average difference	Total (Training-test)	8,071	97.33%	8.64%	69.86%
			2.09%	3.68%	1.68%

Note(s): Classifying parameters: all indicators of significance for each region

Training set: patents issued in months excluding March, June, September and December

Prediction set: patents issued in March, June, September and December

Source(s): Authors' own work

re-examination were filed. There were three significant indicators: number of attached figures, number of words in abstract and examination duration. There were 11 regions that were found to be significant: Region 1 (US), Region 2 (JP), Region 3 (Guangdong), Region 4 (Shenzhen), Region 5 (Jiangsu), Region 6 (Zhejiang), Region 7 (Beijing), Region 8 (DE), Region 9 (Shanghai), Region 12 (CN-others) and Region 13 (Overseas-others).

Average accuracy of model training sets, numbering overall 5,303 China invention patents in 11 significant regions, was 70.43%, and the accuracy ranges for SVM/RBF model training

were from 76.49% in Region 4 (Shenzhen) to 63.14% in Region 8 (DE). Average accuracy of prediction sets, numbering overall 2,768 invention patents in 11 significant regions, was 68.75% and ranged from 72.73% in Region 4 (Shenzhen) to 62.83% in Region 9 (Shanghai).

Average accuracy of SVM/RBF model training for Group 0 comprising 1,661 invention patents in 11 significant regions, which claims are invalid after invalidation re-examination, was 9.87%. Accuracy of SVM/RBF model training ranged from 23.55% in Region 13 (Overseas-others) to 0.00% in Region 8 (DE) and in Region 7 (Beijing). Average prediction accuracy of Group 0, which comprised 839 invention patents, was 6.20%; and accuracy of SVM/RBF prediction ranged from 12.59% in Region 13 (Overseas-others) to 0.00% in Region 9 (Shanghai).

The average accuracy of model training sets of Group 1 comprising 3,642 invention patents in 11 significant regions, which claims are fully or partially valid after invalidation re-examination, was 98.95%. Accuracy of SVM/RBF model training ranged from 100% in Region 7 (Beijing) and in Region 9 (Shanghai) to 95.95% in Region 1 (US). Average prediction accuracy in Group 1 comprising 1,929 invention patents was 95.96%, and the accuracy of SVM/RBF prediction model ranged from 100.00% in Region 7 (Beijing) to 90.78% in Region 13 (Overseas-others).

Figure 3 shows that 8,071 China invention patents in 11 significant regions perform the model training and prediction through SVM/RBF. Training sets contains 5,303 patents issued in months January, February, April, May, July, August, October and November. Prediction sets comprised 2,768 patents issued in March, June, September and December. Accuracy of model training was higher than accuracy of the prediction in every region. Nevertheless, the outcome of the model training ranged from 76.49% to 63.14%, and the average was 70.43%. While prediction outcomes ranged from 72.73% to 62.83%, the average was 68.75%. The average difference between training sets and prediction sets was 1.68%, which proves the feasibility of use of SVM with RBF to train and predict the invalidation re-examination decisions for China invention patents.

Figure 4 depicts the comparison between decision groups through SVM/RBF to perform the model training across 11 significant regions. Accuracy of Group 1 was higher than accuracy of the Group 0. Nevertheless, accuracies for SVM/RBF model training in Group 1, which the claims are all or partially valid after invalidation re-examination, were ranged from 100% in region 7 (Beijing) and in region 9 (Shanghai) to 95.95% in region 1 (US). Accuracies of SVM/RBF model training in Group 0, which claims are invalid after invalidation re-examination, were ranged from 23.55% in region 13 (Overseas-others) to 00.00 in region 8 (DE)%.

Figure 5 shows comparison of accuracy of predictions made by SVM/RBF in different decision groups across 11 significant regions. Accuracy in Group 1 was again higher than of Group 0. Nevertheless, accuracy of SVM/RBF predictions in Group 1 ranged from 100% in Region 7 (Beijing) to 90.78% in Region 13 (Overseas-others). Accuracy of SVM/RBF prediction in Group 0 ranged from 12.59% in Region 13 (Overseas-others) to 00.00% in Region 7 (Beijing), Region 8 (DE) and Region 9 (Shanghai).

Comparison of Figures 4 and 5 shows that accuracy of training sets is better than the prediction sets. Accuracy of training set in case of each significant region in Group 1 was higher than in prediction set. Accuracy in Group 1 training sets ranged from 100% to 95.95%, and the average was 98.95%, while accuracy in prediction sets ranged from 100% to 90.78%, and the average accuracy in Group 1 was 95.96%. The average difference between Group 1 training sets and prediction sets was 2.09%, which again proves the adequacy of SVM with RBF for Group 1 for training and predicting China invalidation re-examination decisions for invention patents.

Accuracy of training sets in Group 0 in each significant region was also higher than the prediction sets accuracy. Accuracy of Group 0 training sets ranged from 23.55% to 0% and the average accuracy was 9.87%. Prediction accuracy ranged from 12.59% to 0.00%, and

the average accuracy in Group 0 was 6.20%. The average difference between Group 0 training sets and prediction sets was 3.68%.

The highest accuracy for both training set and prediction set were in Region 4 (Shenzhen), which were 76.49 and 72.73%, respectively. The highest accuracy of training set and prediction set in Group 1 was in Region 7 (Beijing) with 100%. The highest accuracy for training set and prediction set in Group 0 was in Region 13 (Overseas-others), which were 23.55 and 12.59%, respectively.

Figures 4 and 5, Tables 6 and 7 show that accuracy was much better in Group 1 than in Group 0. The reason could be that Group 1 had much larger samples of training sets and predicting sets.

The above results confirm the adequacy of SVM with RBF for prediction of the invalidation re-examination for China invention patents. Besides being beneficial for predicting patent sustainability, it is helpful to provide strategic support for patent monetization. In particular, Group 1 performed the high accuracy of 98.95% for training sets and 95.96% for prediction sets with average. This research also reveals that accuracy of predicting invalidation re-examination is higher in highly developed cities in China, such as Region 4 (Shenzhen) and Region 7 (Beijing).

5.1 Comparative analysis with previous studies

Intellectual capital encompasses all intangible and knowledge-based assets that an organization leverages to generate value (Kianto *et al.*, 2017). Intellectual property is a crucial asset for companies and serves to raise management's awareness of intellectual capital (Bollen *et al.*, 2005).

Although there has been limited research that has applied artificial intelligence to investigate patent information (Abbas *et al.*, 2014; Baruffaldi *et al.*, 2020; Trappey *et al.*, 2020), machine learning and deep learning to analyze intellectual property information on patent trends and patterns (Aristodemou and Tietze, 2018), patent citation to measure knowledge flow (Alcácer and Gettelman, 2006), corporate developments of scientific publication, patents and trademarks (Dernis *et al.*, 2019). However, this research is the first to apply machine learning for predicting patent validity though SVM with RBF.

How to select appropriate indicators for patents has been discussed in extant literature. For example, patent citations for 24 technologies of US patents were examined by Carpenter and Narin (1983), Relationships between asymmetric litigation-value and patents were studied by Allison *et al.* (2004). Relationships between qualified word counts and validity of 813 European patents were investigated by Reitzi (2004). Confusions among forward citations, patent families, issued decisions, patent oppositions and patent renewals were studied by Zeebroeck (2007). Arts *et al.* (2012) studies 290 US biotechnology patents from 1976 to 2001 for validity based on the involved international patent classification, backward citation, forward citation, the number of claims and the number of non-patent references. Patent citations and the involved international patent classifications as indicators were studied in terms of technology novelty and radical impact by Verhoeven *et al.* (2015).

This research applied 8 meaningful patent indicators and further used ANOVA to prove the significances on 8,666 China invention patents which has filed invalidation re-examination from 2000 to 2021.

5.2 Theoretical implications

The key aspects of machine learning include data preprocessing, feature engineering, model selection and evaluation, model optimization and model interpretability, etc. Machine learning models are often seen as a black box, making it difficult to interpret their results. However, SVM is a supervised machine learning model, and its algorithm is primarily used for classification and regression. RBF can further enhance the capability of SVM. In this research, SVM with RBF is employed to predict the decision of invalidation re-examination for China

invention patents. Nevertheless, this research sample design was divided into valid patent Group 1 and invalid patent Group 0. In addition, the existing invalidation re-examination decisions in these 8,666 China invention patents were applied to validate the outcomes from the training sets and prediction sets through SVM with RBF. Therefore, the strength of SVM with RBF for classification can identify valid or invalid decisions. The outcomes of this research did prove to be an innovative application of SVM with RBF on patent validity. The difficulty of machine learning to interpret the outcome was resolved by comparing the existing invalidation re-examination decisions in these 8,666 China invention patents.

5.3 Practical implications

Patent is one type of intellectual property, which is a subset of Intellectual Capital. Companies with an interest in intellectual capital consider patents for protection of their proprietary research, products and process; and take measures for improving their profitability by leveraging the patents and monetization through different measures. The disclosure of patent information is generally correlated with higher market value for companies (Roos *et al.*, 1997). Regarding the value extraction of intellectual capitals, it involves the development of assets analysis, selling or licensing of the assets, creation of joint venture or alliance, or avoidance of litigations, etc (Sullivan, 1999). Patent sets use limitations and defines the boundaries of a specific piece of knowledge, transforming it into a legal entity. However, patent value must be unpacked and integrated into products or services (Mouritsen and Koleva, 2005). To unlock the value of patents from a strategic view (Rivette and Kline, 2000), sustainability of patents is the core (Smith and Hansen, 2002). This research confirms the application of SVM with RBF model to predict the stability of patents, which is an innovative approach to support intellectual capital management.

5.4 Policy recommendations

In the real world, due to various circumstances, patent examination has not been perfect in different regions or country patent offices. There are measures and procedures for correction as the remedy. For example, the American Invents Act (AIA) in the United States, appeal boards in patent offices or patent courts are designed for certain countries, such as Germany, Korea, Japan, China and Taiwan. For compliance with domestic policies, regulations and laws, corporates can benefit from this research by applying SVM with RBF as internal quality checks of their existing patents, as cost-effective measure for assessing the value of their intellectual capitals. If a patent is predicted to be invalid, the maintenance fee can be waived and it can be reallocate for better usages. While confronting the attack by challenging the invalidation re-examination, patent owner can apply SVM with RBF to predict patent sustainability and adjust strategy, taking steps such as amending the patent claims for survival, litigation tactics, settlement negotiation, cross-licensing, joint venture or alliance with the counter parties.

5.5 Limitations of the study

This research was limited to 8,666 China invention patents which faced invalidation re-examination from 2000 to 2021. There will be future studies on other types of patents, such as utility model patents or design patents for a wider range of patent rights. Due to the availability of data sets, this empirical approach through SVM with RBF to predict a patent stability was limited to patents in China, however, patents in US, Europe or other Asian regions can be studied in the future.

Patent is a legitimate type of intellectual capital. Patent monetization, such as licensing, trading or litigation, can create extra revenue for corporate even before the related products or services are put on the market. However, the patentability must be certain. In the past, patent owners were unable to predict patentability. If patent disputes arises, patent owner can only

wait till the decision from patent office or court, which can consume enormous time and resources. This research proves machine learning model, SVM with RBF to predict sustainability of China invention patents as a breakthrough approach and its practical application for intellectual capital.

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